Dynamical Aspects of Knowledge Evolution

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Tracking Changes in Knowledge Bases

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Abstract. Undeniably, in this rapidly changing world some knowledge granules change over time. Tracking these changes seems to be one of the most crucial processes in knowledge management. Every potential change is a result of knowledge adoption and application to solve a given problem or task in particular domains. However, there is a lack of a model that provides an event-driven framework, along with the core adoption process explicitly expressed with related factors, which together serve as an efficient tool to adopt and reuse knowledge on one hand, while on the other, to measure and evaluate the various aspects of knowledge quality and usefulness. This paper aims to fill this gap by introducing a knowledge adoption process and an ontology-aided encapsulation knowledge (OAKE) model. While the former breaks down the tacit adoption process into two explicit sub-processes and measurable factors, the latter exposes knowledge evolution over time by a sequence of recorded events.

Keywords: knowledge, dynamics, evolution, adoption, management.

1 Introduction

"Tacit, complex knowledge, developed and internalized by the knower over a long period of time, is almost impossible to reproduce in a document or database. Such knowledge incorporates so much accrued and embedded learning that its rules may be impossible to separate from how an individual acts" [1].

Moreover, considering the issue of knowledge reproduction, one could ask: how does knowledge change over time, and what are the origins and reasons of the occurring changes? Similarly, advanced-in-age knowledge has accumulated so many changes as a result of the cognition of its nature and has been so enriched by learning that its evolution may be impossible to reconstruct.

Knowledge is a wide and abstract term, which has been the subject of an epistemological discussion of western philosophers since times of ancient Greece. Since the second half of XX century, knowledge has been widely studied in numerous research papers, uncovering many definitions, contexts and phenomena and in the end leading to a legitimate new scientific discipline, defined as knowledge management [2,3,4]. For an organization, knowledge has become the most powerful leverage to achieve a competitive advantage, therefore it is crucial to effectively manage own resources [5,6,7].

These days, people and machines produce countless volumes of data and information, consciously and intentionally transformed into knowledge. All of the aforementioned are important assets in knowledge-driven environments and the last is by far the most labour- and time-consuming [8,9,10]. In consequence, some employees spend the majority of their working hours doing manual, high-demanding intellectual work, supported by computers processing and manipulating large amounts of data as an input, and producing information or even knowledge as an output [11,12,13]. As a result, a new concept of an employee was coined: "a knowledge worker", whose job primarily involves the creation, distribution and application of knowledge [14]. By many, Peter Drucker is credited to be the first to use this term in his 1959 book, "Landmarks of Tomorrow" [15,16].

Data sets encoded in a computer memory differ in format, size and type. In general use, there are two primary data formats: binary and text, and four primary data types: text, drawing, movie and voice. Ordered sequences of characters, images and spoken words are perceived as explicit and unique information objects. Here, we can point out objects that are in everyday use, such as documents, presentations and spreadsheets, email-, voice- and video- messages, and web-blogs, forums and pages. Each object processed and interpreted by an individual human mind, applicable and legitimate in a specified environment, where the consequences of the application are known or can be predicted, is considered to be a knowledge object. All of these objects, gathered and redacted, cleaned and re-processed, organized and integrated in one consistent repository, along with a user interface that facilitates SCRUD operations (an acronym for search, create, read and delete), constitute a unified platform for knowledge workers.

However, knowledge workers are still looking for a comprehensive solution to manage knowledge in such a manner that it will not only serve as pure technology but also provide interaction with other humans and available resources [17,18,19]. At present, in the development of knowledge management (KM), to the best of our knowledge, there is a lack of a consensual framework, or generic process model, for tracking knowledge evolution; instead, to some extent, each organization follows its own set of principles, design criteria and practices in this area. Most existing frameworks and tools broadly touch the area of KM, and only a few are targeted specifically at tracking knowledge evolution. This paper aims to fill this gap by proposing an ontology-aided knowledge encapsulation (OAKE) model, along with a knowledge cognition model.

The rest of the paper is organized as follows. The literature review is given in Section 2. In Section 3, at first, the knowledge cognition model is introduced followed by the OAKE model. Final conclusions are included in Section 4.

2 Literature review

The recent interest in knowledge management (KM), observed both in business and science, is nothing new. Therefore, it is no secret that nowadays, information and communication technologies (ICT) are the basic means to efficiently support every phase of the KM process. However, diverse technologies, such as knowledge management systems, knowledge discovery systems and knowledge-based systems are currently working with different types of knowledge [20,21,22]. In our paper knowledge management is a term for any operations focused on knowledge granulas embracing all typical phases: discovering, registering, transformation and utilization. Another words, KM is a discipline that covers ideas and concepts from a variety of other disciplines, including artificial intelligence, data mining, distributed databases, information systems, intellectual capital and innovation [23,24,25].

Knowledge management is the process of continually managing knowledge of all kinds to meet existing and emerging needs, to identify and exploit existing and acquired knowledge assets and to develop new opportunities [26]. From a practical business perspective, it is a deliberate, systematic business optimization strategy that selects, distills, stores, organizes, packages, and communicates information essential to the business of a company in a manner that improves employee performance and corporate competitiveness [27]. In a narrow sense, it can be defined as a set of principles, processes, and techniques leading to the creation, organization, distribution, use and exploitation of knowledge [28,29]. Crucial for the defined paper topic seems to be consideration of the phases directly connected with knowledge dynamics. In the next sections these selected KM operations will be discussed.

2.1 Knowledge transformation

There are two basic forms of knowledge: tacit and explicit [30,31]. The former refers to that which is unarticulated, undocumented and held in peoples' heads, while the latter is expressed, structured, codified and accessible for those other than the individuals originating it [32]. Thus, knowledge exists on the spectrum of these extremes and its transformation means moving from one extreme to another [33,34,35].

There are many reasons to engage means to perform knowledge transformation. The same or very similar problems do not need to be solved again – the particular pieces of knowledge can be reused. Effective reuse is apparently related to the effectiveness of the organization [36], and is an even more frequent concern when compared to knowledge creation, being viewed as somehow more important and difficult to manage [37]. In the theory of knowledge reusability, Markus [38] emphasizes the role of knowledge management systems and knowledge repositories, often called organizational memory systems, in the efficient preservation of "intellectual capital" [39,40,41]. Basically, knowledge transformation process can be identified with changing of existing knowledge or even with its creation applying for example process-driven approaches [42,43,44].

2.2 Knowledge codification

The codification of knowledge is the process of converting knowledge into a form in which it can be handled by particular technology to store, transfer and share it [45]. In addition, it makes knowledge visible, accessible and usable in a form and a structure meaningful to the user [46]. Note, the knowledge code used during implementation (moving to a computer memory) is crucial to evaluate its usefulness and appropriateness. Coded knowledge should have a unique identity and an adequate form of representation, such as a rule, a decision table or tree, a model for problem solving and case-based reasoning or a knowledge map. To store and disseminate knowledge across an organization, various IT technologies, such as databases [47], intranets [48,49] and business intelligence tools, are usually put into action [50,51,52]. In such a context the codification phase can be considered as the supporting operation of knowledge transformation but stressing its more technological nature [53,54,55].

2.3 Knowledge adoption and reuse

Knowledge adoption concerns an internalization phase of organizational knowledge transfer [56], in which explicit information is transformed into internalized knowledge and meaning [57]. In general, adoption usually begins with the recognition of the need for information, then moves to searching in possessed repositories, next to the initial decision to accept the received information, followed by validation in practice, and ending with absorption. On the other hand, knowledge provides the means to analyze and understand data and information [58,59,60], delivering the circumstances for an internal agreement between what we know and what we want to know.

The process of knowledge reuse consists of the following phases: capturing, packaging, distributing and reusing [38,61]. In the human mind, the latter involves both recall and recognition, while the former concerns information attributes, such as: the author, the date of creation, the representation form, and eventually the storage location. Moreover, the latter tries to determine the relevance degree of the incoming information, and possibly append it to pending knowledge to be applied again [62].

Retained and reused knowledge can improve project management capabilities [63], support managers in the decision-making process [64,65,66] and guide the product design [67]. To be innovative and develop novel products and services, organizations need to gain knowledge of both external and internal worlds [68,69]. To achieve these ends, the principal goal should be to focus on tracking changes occurring in internal bodies of knowledge.

3. Ontology-Aided Knowledge Encapsulation Model

All the mentioned knowledge phases are crucial in the created models supporting its dynamicity. In order to define a concept useful in modelling dynamical aspects of knowledge important assumptions should be declared. The name of the elaborated model comes from a conscious merger of the major concepts involved. Though the first term – ontology-aided may be unquestionable, while the term – encapsulation needs to tell a brief story. By definition, data and any appropriate operations should be grouped together i.e. encapsulated, and the implementation details of both should be hidden from the users [70]. A similar assumption was made in the elaborated model, where an operation is featured by an event. To implement the TBox part of the ontology, i.e. terminological knowledge declared as axioms and defined by a set of concepts and roles (the global axioms and core taxonomy), the Cognitum Ontorion system was used with the built-in capability of English semi-natural language support [55,71].

This section begins with a description of the prior model, which provides the operational foundation for the later model.

3.1 The knowledge adoption model

Knowledge adoption has been defined in many different ways. Beesley and Cooper [72] defined it as “identification of new products, services, markets, or processes”, while Brown [73] as “the means through which policy-makers digest, accept then ‘take on board’ research finding”. However, to the best of our knowledge, none of them does not reflect the general idea laying behind the nature of the process. Thus, for us, knowledge adoption means the acceptance of the state about the way things are and how they work, followed by the confirmation and judgment of its significance and value in the frame of present context and individual beliefs [31,74].

These two actions we have previously defined as verification and evaluation – both included to more universal term: validation, respectively [12,75]. For others, the former refers to reaching an agreement over the meaning of a term [76], involving concept matching and relation comparison [77,78], while the latter refers to the evaluation of quality and usefulness [79,80].

In terms of knowledge verification, three factors have been distinguished: adequacy, completeness and consistency [81]. The first factor corresponds to the degree of applicability or relevance to a given problem or task, the second refers to the degree to which the knowledge for completing a task or making a decision is passable and available, and the third refers to the degree of a logical match between the object and the content. In terms of knowledge evaluation, two factors have been identified: reliability and effectiveness. Both factors concern some kind of knowledge assessment, while the former reflects a degree of agreement to self-beliefs and experience, the latter refers to the outcomes of the applied knowledge.

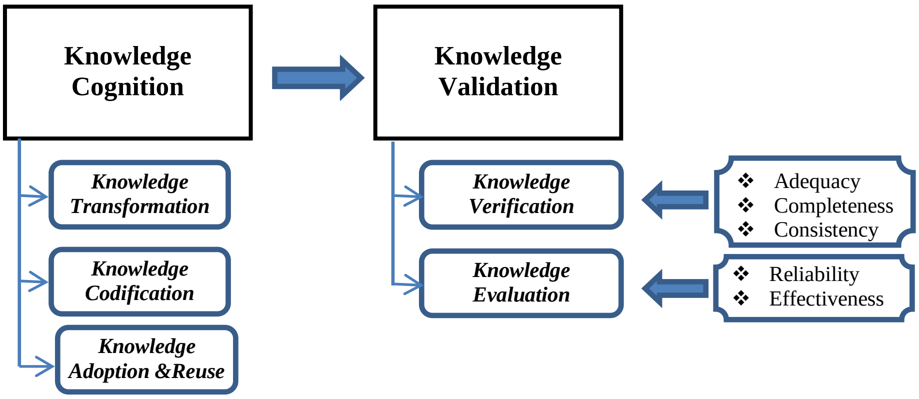

Fig. 1. The model of the knowledge adoption process (KAP)

These general factors can be expanded and elucidated in the form of interpretable numeric, logic or fuzzy metrics, to an extent appropriate to the context and the size of the knowledge object. If some errors, obstacles and constraints are observed, a need for change in a body of knowledge occurs.

3.2. The OAKE model

The objective is neither to introduce a model which outlines all possible phases, tasks or relationships underlying the knowledge evolution process, nor to set up a strict list of guidelines to follow which positively affect organizational performance. Instead, the model highlights a few major factors that can expose the origins of and reasons for the occurred changes in particular bodies of knowledge over time (Fig. 2).

The aim of building the model is to capture changes in such a way that allows us to query and infer from the gathered knowledge. It is based on the observations collected from a requirements elicitation project for virtual on-line agents, where different groups of stakeholders, during the development of the knowledge base, reported heterogeneous requests to include itemized changes, often comparable or self-conflicting.

Each change is represented by a unique event, performed by a knowledge worker on the knowledge object. The notion of a single event is structured and formalized in the form of an ontology that provides a common understanding of performed operations and perceived observations.

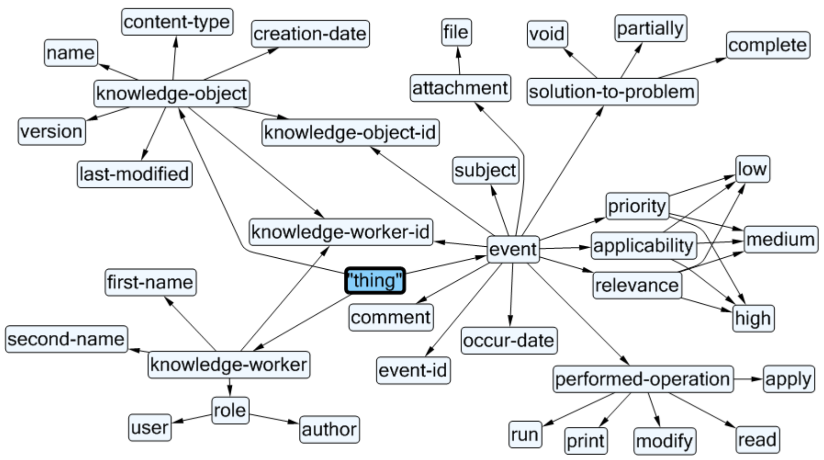

Fig. 2. The OAKE Model

Each single event object has a unique identifier and occurrence date, both automatically generated by the system. A knowledge worker inputs the subject that should generally reflect the idea laying beyond the event. Next, a type of performed operation on the knowledge object is selected, where a set of five options are available in multiple choice (apply, modify, read, run, print). The degree of priority, applicability and relevance are assigned, where each can be defined as low, medium or high. Next, a knowledge worker points to what degree (void, partially, complete) he found a solution to a problem or a task in the particular knowledge object and, if necessary, can also add a comment and attach a file. The event object is connected through two separate relations with the knowledge object and the knowledge worker.

The knowledge object has a name that, specified by a user, should reflect its content in general terms, as well as an accurate type in which the information is encoded for storage in a computer file. The creation date is a predefined property that corresponds to the date of the first version, while the last modified property shows the date where the last changes were made. A built-in mechanism provides unique version numbers for unique states of knowledge objects, assigned in increasing order to new developments.

The knowledge worker is identified by their first and second name and may play two different roles: an author (a creator) of the knowledge object, responsible for the quality of its content by admission and including incoming changes, or a user who simply utilizes available knowledge objects in the decision-making processes.

The history of changes is not visible in the knowledge object; however, they are stored in the ABox part of the ontology. This mirror of knowledge evolution over time facilities various evaluations which contribute to the refinement of existing knowledge and to the production of new knowledge. A concept of implementation of changes is demonstrated in the next section.

4. Knowledge dynamics

The capture of ontology changes is triggered by either [82]:

- changes in the domain,
- changes in the shared conceptualization,
- changes in the ontology specification.

The first type is known from the area of the database schema versioning. Domain evolution, reflected and described by the changes, concern seven different facets [83]:

- heterogeneous instances: over time different occurrences of the same value have different meanings in a domain extension; for instance, if the organization merge or split departments, then the preserved naming represent a different set of resources (e.g. employees, faculties);
- cardinality changes: in particular, cardinality relationships between domains might also change over time; in other words, the number of occurrences in one entity which are associated to the number of occurrences in another are not always constant; for example, a *1-to-n* relationship between departments and faculties may be changed to *m-to-n* as a result of new legal regulations;
- granularity transition: from existing population values, having different granularity, might be added to a domain extension; for instance, the numeration of rooms or buildings might be changed due to the merge or acquisition [84,85];
- encoding changes: particular values might have also encoded meaning, which neither is known, nor provided elsewhere; for example, the naming of projects successfully delivered are eventually different from the others (failed, cancelled, etc.; see [86]);
- time zone and unit differences: organization sites use local time zone and units which globally differ; thus directly comparing such values may be irrelevant;
- identifier changes: the organization needs changes over time; as a consequence the indexing strategies may also change over time, leading in parallel or overlapping naming schemas; for instance, the codes of the products, previously 4-

digits numbers, now having additional 6 zeros, are different for both the users and IT systems;

- field recycling: in some systems it is difficult or even infeasible to alter certain database properties; in this case there might be a need to shrink the database or even implement a new instance with a different naming schema, replacing the existing ones; for example, a company might shift from hierarchical to a matrix structures, remodeling data structures [87,88,89].

The second type of the source of the ontology changes concern the assumption of the static nature of the shared conceptualization. Nowadays, it is at least naive to define specification in terms of the fixed settings, undeniably constant over time. On the contrary, many studies describe ontologies as dynamic networks of meaning [90,91,92].

Eventually, the third type is associated with ontology encoding, which may vary in types and formats. Along with ontology evolution, engineers are currently facing also the issue of merging ontologies [93,94,95].

In order to tracking of changes ontology presented in the OAKE model we reduce list of objects (Fig. 3).

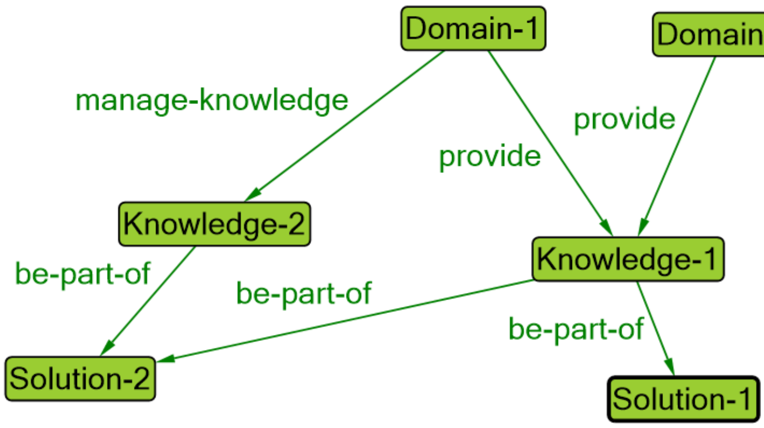

Fig.3. Initial stage of the partially incorporated OAKE model

The most important objects are placed in the Figure; previously defined relationships are actual: Knowledge, Domains and Solutions. Assuming changes in the Domains the discussed ontology is presented in Fig.4.

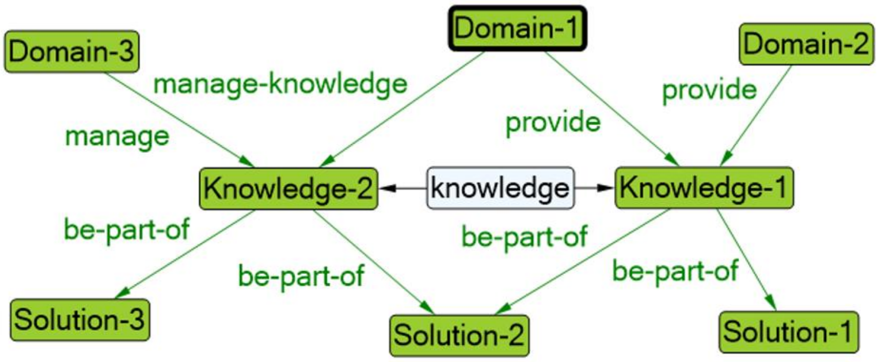

Fig.4. Final stage of the partially incorporated OAKE model

List of the defined categories has been extended as a result of knowledge dynamics; next specimens appeared in case of Domains and Solutions and particular relationships mapped these new items. Comparing gradually appearing versions of ontology we are able to monitor knowledge dynamics supporting new solutions and taking into account new domains.

5. Conclusions

This paper introduces two models which bring a contribution to the discipline of knowledge management. Both are the effect of broadly self-conducted research and participation in other research projects, supported by a critical analysis of literature, narrowed down to major concepts and those highly related with the discussed subject.

The OAKE model, presented here, incorporates events with knowledge objects and workers, and exposes knowledge evolution over time on one hand, while on the other hand, is a baseline to measure and evaluate the various aspects of knowledge quality and usefulness.

The knowledge cognition model breaks down the tacit cognition process into two explicit sub-processes and measurable factors. It is, ipso facto, an attempt to unambiguously generalize the spectrum of cognitive processes inherently processed in an individual human mind.

A retrospective view of the elaborated models gives the impression that each of them can be independently adopted to any extent and in any application domain. However, both only embody general concepts with a high degree of abstraction, but not biased at any level, and can be further extended and attributed, eventually providing a framework to adopt and reuse knowledge with support for event-based tracking of changes.

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